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Long Term Wind Turbine Performance Analysis Through SCADA Data: A Case Study

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Abstract

Performance monitoring of horizontal-axis wind turbines is a complex task because they operate under non-stationary conditions. Furthermore, in real-world applications, there can be data quality issues because the free stream wind speed is reconstructed through a nacelle transfer function from cup anemometers measurements collected behind the rotor span. Given these matters of fact, one of the objectives of the present work is applying an innovative method for correcting the nacelle wind speed measurements, which is based on the manufacturer power curve and statistical considerations. Three operating wind turbines, having 2 MW of rated power and owned by the ENGIE Italia company, are contemplated as test cases. Operation data spanning ten years (2011-2020) are studied: actually, this work aims as well at contributing to the methods for estimating the performance decline with age of wind turbines, basing on long term SCADA data analysis. The raw and corrected wind speed measurements are fed as input to a Support Vector Regression for the power curve: by selecting appropriately the training and validation data sets, it is possible to estimate the average yearly rate of performance decline. Using the corrected wind speed, the estimate obtained in this study is compatible with the most recent findings in the literature, which indicate a -0.17% decline per year.

wind energy, wind turbines, monitoring, data analysis, wind speed correction, manufacturer power curve.

1 Introduction

In last decade, the renewable energy sources rapidly spread due to the increasing energy consumption and the strict environmental requirements. In this context, two of the most diffused technologies to increase the self-sufficiency of residential or industrial users [1] are photovoltaic generators [2] and Wind Turbines (WTs). Horizontal-axis WTs are rotating machines operating under non-stationary conditions, because the source is stochastic. Therefore, monitoring their performance is a non-trivial task.

Typically, well established models of industrial wind turbines have design specifications in the form of reference curves for the thrust coefficient and the power coefficient as a function of the longitudinal wind intensity v. The power curve [3] is the most employed method for monitoring wind turbine operation, because of its intuitiveness: substantially it is a scatter plot with the input (wind intensity v) in abscissa and the output (produced power P) in ordinates.

There is a substantial mismatch between the power curve from design specifications (a line) and a real-world power curve (a cloud of points): then, a critical point of performance monitoring is understanding how to interpret real-world power curves in relation to design power curves.

The fundamental reason why there is mismatch between a design power curve and a real-world power curve is that the former employs in abscissa the longitudinal free stream wind speed v, while the latter employs a reconstruction of the free stream wind speed through a nacelle transfer function which elaborates the measurements from the anemometer (typically, cup) placed behind the rotor span. It is a well-known matter of fact that wind shear, turbulence intensity, atmospheric stability affect the nacelle transfer function [4, 5].

Basing on these considerations, it is complicated to argue if an apparent deviation from nominal behavior of a wind turbine is due to non-optimal functioning or is due to the fact that the real free stream wind speed (which is not measurable in practice) is different from the estimate provided by the nacelle transfer function at the particular occurring conditions of temperature, wind shear, turbulence, and so on.

This premise poses the motivations of one qualifying point of this study, which aims at contributing to the methodologies for reducing the mismatch between the design specifications and the nacelle anemometer measurements through an innovative calibration of the latter, based on statistical considerations. In literature, the most applied techniques to correct the anemometer measurements are two [6], [7]. However, these corrections require additional information by a meteorology mast close to the turbines, i.e. the measurement of an unperturbed wind stream in their neighbourhood. This information is missing in most of wind power plants, and, in such conditions, these corrections cannot be applied. On the contrary, the present work applies an innovative method [8], based on the manufacturer power curve only, to correct wind speed data. As a consequence, it can be applied to the turbines in any wind farm.

Furthermore, in this study, the analysis of wind turbine power curve is considered in the context of a topic which has been recently attracting a remarkable attention in the literature: how does wind turbine performance decline with age [9–15]? Actually, it is a common sense expectation that the performance of wind turbines should decline with age, similarly to what happens for most technical systems [16], but there are no theoretical estimates for quantifying how much.

Due to the fact that a vast number of wind turbines, especially in Europe, is reaching the end of the expected lifetime [17], it becomes possible to analyze long SCADA data sets (order of a decade of data), in order to quantify the decline trend. This calls for the development of ad hoc SCADA data analysis techniques and the present study aims at furnishing a contribution to this objective as well.

The study is organized as a real world test case discussion: ten years of SCADA data from a wind farm owned by ENGIE Italia, featuring 2 MW wind turbines, are analyzed. The estimate of the performance decline with age is achieved by passing through a Support Vector Regression with Gaussian Kernel for the power curve: by training and validating the model with data sets appropriately selected, the estimate of aging can be elaborated from the residuals between model estimates and measurements. In this analysis, the nacelle anemometer data and the data renormalized according to the above cited procedure are both employed, in order to inquire how much the aging estimates can be biased by wind speed measurement issues.

The structure of the manuscript is the following: in Section 2, the test case and the data set are described; Section 3 is devoted to the description of the methods; the results are collected and discussed in Section 4; conclusions are drawn in Section 5.

2 The test case and the data set

The selected test case is composed by three wind turbines having 2 MW of rated power, owned by the ENGIE Italia company and sited in southern Italy. Data from 1st January 2011 to 31th December 2020 have been at disposal for this study. The sampling time is 10 minutes and the data have been divided in yearly packets for the analysis.

The list of available SCADA measurements is the following:

- Nacelle wind speed v (m/s);
- Ambient Temperature T (K);

- Blade pitch angle $\beta(°)$;
- Power production P (kW).

Data have been filtered on wind turbine operation using the appropriate run time counter and outliers have been filtered using the average wind speed - blade pitch curve. Furthermore, only data below rated power are kept because the monitoring problem becomes trivial at rated power.

An important information about the test case wind turbines is that the rotational speed control has been optimized in 2018, as typically happens during the lifetime of a wind turbine, and their performance is therefore expected to improve since then.

3 Method

3.1 Description of Nacelle Wind Speed Correction Method

The proposed method aims to correctly evaluate the performance of WTs starting from the manufacturer power curve and the wind speed measured by the turbine anemometer. In particular, this approach assumes the manufacturer curve to be the locus of the best performance for the WT under analysis. Thus, for a certain wind speed, the power provided by the manufacturer is the the maximum value that can be achieved. The result of the method is an analytical equation to assess, for each detected wind speed, the corresponding value at the entrance of the WT rotor. In particular, the procedure consists of the following steps:

- STEP A. Normalization of wind speed to conditions of reference air density. The power curve by the manufacturer is evaluated in reference conditions ($\rho_{\mathrm{ref}} = 1.225$ kg/m^3 at 0 m above sea level and 15°C). However, experimental conditions are different, and data need to be normalized in order to be compared with manufacturer curve. Therefore, experimental data are corrected using the following equation, valid for WTs with active power control:

$$v_{\mathrm{WT}} = v \cdot (\rho_{\mathrm{air}}/\rho_{\mathrm{ref}})^{1/3} \tag{1}$$

  where v_{WT} is the wind speed corrected to the conditions of reference air density, and ρ_{air} is the air density during measurements.

- STEP B. Removal of measurements with turbulence intensity larger than 10% [18]. Experimental data are acquired during a constant time interval (10 min in this work). For each measurement, the turbulence intensity is evaluated, being the ratio between the standard deviation of the wind speed and the average value in the same time interval [19].

- STEP C. Selection of the dataset S_{k}. A generic working point k is selected from the manufacturer power curve, with power P_{k} and wind speed v_{k}. Then, the dataset containing experimental measurements in the neighbourhood of P_{k} is identified. This dataset includes the experimental data with electric power in the range $P_{\mathrm{k}} \cdot (1-\epsilon)$ and $P_{\mathrm{k}} \cdot (1+\epsilon)$. In this paper, $\epsilon = 0.01$. The dataset S_{k} has the following mathematical formulation:

$$\begin{aligned} S_{\mathrm{k}}\{(v_{\mathrm{WT,i}}, P(v_{\mathrm{WT,i}})) : P(v_{\mathrm{WT,i}}) \in \\ [P_{\mathrm{k}} \cdot (1-\epsilon), P_{\mathrm{k}} \cdot (1+\epsilon)]\} \end{aligned} \tag{2}$$

- STEP D. Calculation of the Empiric Cumulative Distribution Function (ECDF) for the selected wind speed v_{k}. For each v_{k} from the manufacture power curve, an approximation of the ECDF is computed. In this method, the Probability Density Function (PDF) of the factorial function Γ is used to approximate the ECDF and it is defined in the following way:

$$f(v) = \frac{v_{\mathrm{k}}^{a-1}}{b^a \cdot \Gamma(a)} \cdot e^{-\frac{v}{b}} \quad (v_{\mathrm{k}} \geq 0) \tag{3}$$

  where $\Gamma(a)$ is the gamma function for the parameter a [20], a is the ratio between the square of the mean value of S_{k} and the square of the standard deviation for S_{k}.

  Finally, the parameter b is the ratio between the mean value of S_{k} and a.

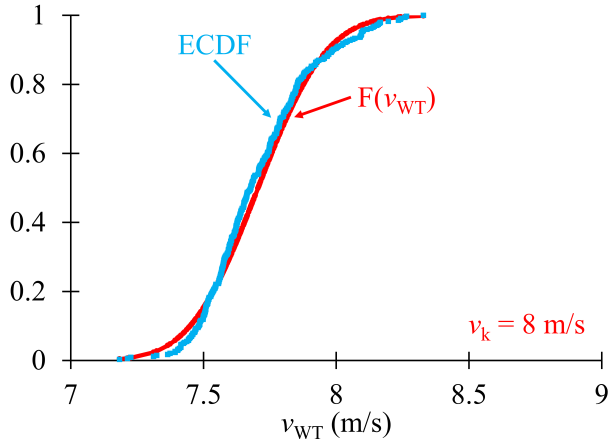

Figure 1: ECDF and PDF evaluated for $v_k = 8m/s$.

- STEP E. Identification of the wind speed fifth percentile. According to the PDF $f(v)$, the fifth percentile $v_k^{5\%}$ is selected in the dataset. This quantity has the 5% probability to not be exceeded, i.e. it is lower than 95% of wind speeds in S_k. The value 5% is identified according to the uncertainty of a typical WT measurement system. Steps C-E are repeated for each wind speed v_k and power P_k in the power curve by the manufacturer.
- STEP F. Linear regression. An equation is obtained through a linear regression to describe v_k as a function of the corresponding wind speed fifth percentile $v_k^{5\%}$. The quality of the linear regression is estimated with the parameter R^2, ranging between 0 (worst model) and 1 (best model).

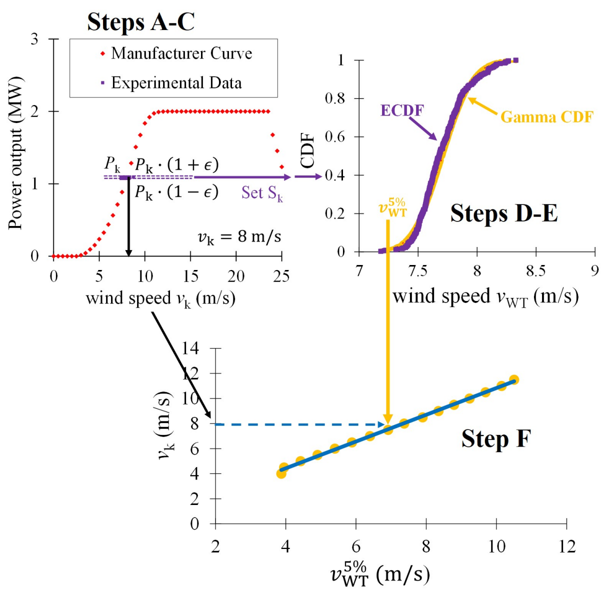

Figure 2: Scheme of the correction method.

3.2 Support Vector Regression

The principles of Support Vector Regression can be illustrated by starting from a linear model, which is posed in Equation 4:

$$y = \boldsymbol{x}\beta + \epsilon, \tag{4}$$

where β are the regression coefficients, which have to be estimated from the input variables data matrix $\boldsymbol{x}$ and the output vector y.

The Support Vector Regression is substantially a constrained optimization problem, because the aim is having the minimum norm of $\beta'\beta$, subjected to the request that the residuals between the measurements y and the model estimate $f(\boldsymbol{x})$ are lower than a threshold ϵ for each n-th observation (Equation 5):

$$|y_n - \boldsymbol{x}_n\beta + b_n| \leq \epsilon. \tag{5}$$

In the Lagrange dual formulation, the function to minimize is $L(\alpha)$, given in Equation 6:

$$\begin{aligned} L(\alpha) = \frac{1}{2}\sum_{i=1}^{N}\sum_{j=1}^{N}(\alpha_i - \alpha_i^*)\left(\alpha_j - \alpha_j^*\right)\boldsymbol{x}_i'\boldsymbol{x}_j + \\ + \epsilon\sum_{i=1}^{N}(\alpha_i + \alpha_i^*) + \sum_{i=1}^{N} y_i(\alpha_i^* - \alpha_i), \end{aligned} \tag{6}$$

with the constraints (Equation 7)

$$\begin{aligned} \sum_{n=1}^{N}(\alpha_n - \alpha_n^*) = 0 \\ 0 \leq \alpha_n \leq C \\ 0 \leq \alpha_n^* \leq C, \end{aligned} \tag{7}$$

where C is the box constraint.

The estimate of the β parameters in terms of the input variables matrix $\boldsymbol{x}$ and of the coefficients α_n or α_n^* is given in Equation 8:

$$\beta = \sum_{n=1}^{N}(\alpha_n - \alpha_n^*)\boldsymbol{x}_n. \tag{8}$$

The non-vanishing α or α^* coefficients are associated to a selection of the most meaningful input observations, hence denoted as support vectors.

Given new input variables $\boldsymbol{x'}$, the regression can be used as in Equation 9 to predict the output:

$$f(\boldsymbol{x}) = \sum_{n=1}^{N}(\alpha_n - \alpha_n^*)\boldsymbol{x}_n'\boldsymbol{x} + \boldsymbol{b}. \tag{9}$$

A non-linear Support Vector Regression is obtained by replacing the products between the observations matrix with a non-linear Kernel function (Equation 10):

$$G(\boldsymbol{x}_1, \boldsymbol{x}_2) = \langle\varphi(\boldsymbol{x}_1)\,\varphi(\boldsymbol{x}_2)\rangle, \tag{10}$$

where φ is a transformation mapping the $\boldsymbol{x}$ observations into the feature space.

A Gaussian Kernel selection is given in Equation 11:

$$G(\boldsymbol{x}_i, \boldsymbol{x}_j) = e^{-\kappa\|\boldsymbol{x}_i - \boldsymbol{x}_j\|^2}, \tag{11}$$

where κ is the Kernel scale.

Then Equation 6 rewrites as in Equation 12:

$$\begin{aligned} L(\alpha) = \frac{1}{2}\sum_{i=1}^{N}\sum_{j=1}^{N}(\alpha_i - \alpha_i^*)\left(\alpha_j - \alpha_j^*\right)G(\boldsymbol{x}_i, \boldsymbol{x}_j) + \\ + \epsilon\sum_{i=1}^{N}(\alpha_i + \alpha_i^*) + \sum_{i=1}^{N} y_i(\alpha_i^* - \alpha_i), \end{aligned} \tag{12}$$

and Equation 9 for predicting rewrites as in Equation 13:

$$f(\boldsymbol{x}) = \sum_{n=1}^{N}(\alpha_n - \alpha_n^*)\,G(\boldsymbol{x}_n, \boldsymbol{x}) + \boldsymbol{b}. \tag{13}$$

In this work, the hyperparameters of the regression κ, C, ϵ have been automatically optimized through 10-fold cross validation.

The input of the Support Vector Regression is the nacelle wind speed (corrected according to Section 3.1 or not) and the output is the power of the target wind turbine: substantially, we use the Support Vector Regression with Gaussian Kernel for modelling the power curve, because of the non-linear relation between wind intensity and power output.

3.3 Estimate of the aging

The use of the Support Vector Regression for estimate of aging goes as follows:

- Select a target data set (e.g. a year);
- Pick as reference the data set corresponding to the year previous the target;
- Use the reference data set for training the Support Vector Regression;
- Simulate the power P for the target data set, given the input v;
- Compute the difference between the measured total energy and the estimate which is based on the model trained with the behavior of the previous year. The metric Δ is given in Equation 14:

$$\Delta = 100 \left(1 - \frac{E_{sim}}{E_{meas}}\right), \tag{14}$$

4 Results

4.1 Correction of the nacelle wind speed

Figure 3 presents the electric power acquired by WT sensors (green dots) and the power curve by the manufacturer (red line) for one turbine in 2019. In this figure, limited to the wind speed range $4-13$ m/s, measurements are not corrected, and a huge number of observations are to the left of the red curve. This performance is not realistic because WTs cannot outperform the manufacturer declaration. This is due to the selection of wind speeds detected behind the WT rotor, while the manufacturer curve is provided evaluating wind speeds at the rotor entrance. As a consequence, the latter ones refer to the unperturbed stream tube entering in the WT rotor, i.e. with larger kinetic energy with respect to the flow behind it. Hence, a correction of wind speeds by WT anemometer is required to compare experimental data with manufacturer curve. Figure 4 reports the results after the correction: experimental data are to the right of the manufacturer curve. Thus, results after correction confirm that the WT does not outperform the manufacturer curve in the wind speed range.

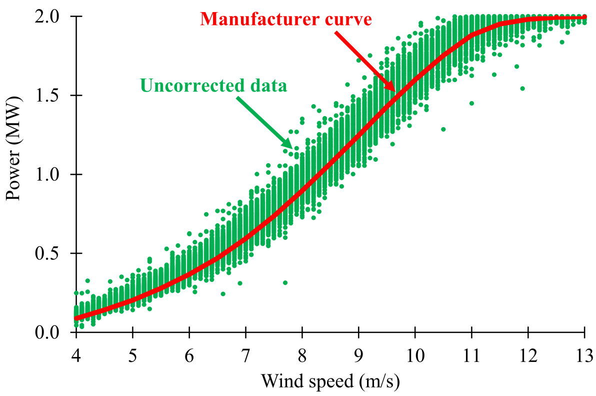

Figure 3: Uncorrected data vs manufacturer power curve.

Generally, this methodology is more effective at medium/high wind speeds due to the lack of observations at low speeds. In this case, the correction properly performs in the full range 4-13 m/s ($R^2 \sim 1$): it is particularly effective at wind speeds > 8 m/s, although its behavior at lower wind speeds is good as well. Similar outcomes are obtained applying the correction method to the other turbines in the different years of the measurement campaign.

4.2 Estimate of the aging

In Figure 5 and 6, average power curves for all the data sets at disposal have been reported for a sample wind turbine, using respectively the nacelle wind speed and the corrected wind speed. From these

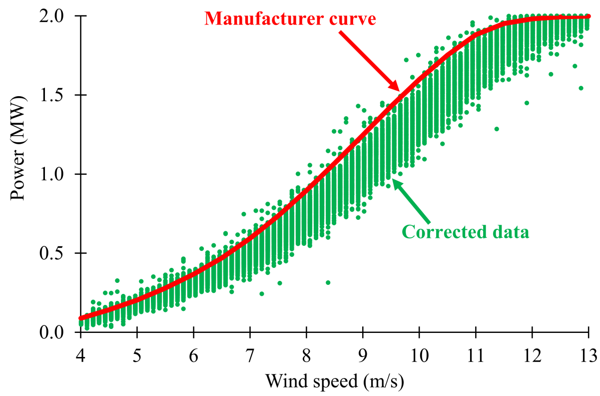

Figure 4: Corrected data vs manufacturer power curve.

Figures, it arises that the power curves for the various years are hardly distinguishable by a qualitative point of view: therefore, for estimating the potential performance decline rate, it is unavoidable to employ methods as those depicted in Sections 3.2-3.3.

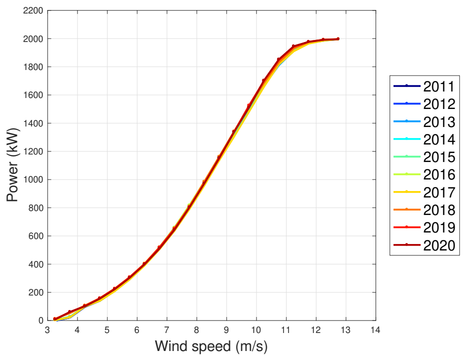

Figure 5: Average power curve of T1 without nacelle wind speed correction.

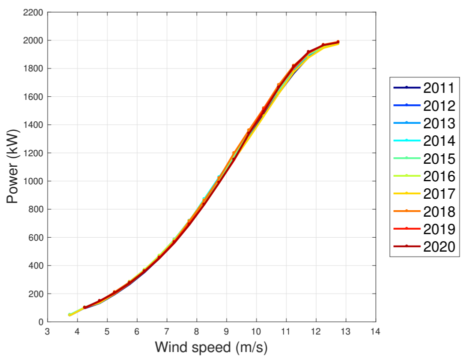

Figure 6: Average power curve of T1 upon nacelle wind speed correction.

Tables 1 and 2 summarize the estimates of aging, obtained using the Support Vector Regression as indicated in Section 3.3. It arises that the two estimates can be noticeably different on a yearly basis, but the essential aspects are captured similarly: there is a sharp worsening in 2017 and an improvement in 2018 due to the control optimization, which more than compensates the previous worsening.

Given this, in Tables 1 and 2, the estimated rate of performance decline with age has been averaged separately for the ten years span and up to 2017. It arises that the estimates obtained with the corrected wind speed are more in line with the most recent findings in the literature [11], because for two out of three wind turbines the computed rate is -0.2% per year. Instead, the estimate based on the nacelle wind speed indicates that the average rate of performance change is positive along the ten years span and up to 2017: despite these wind turbines have not been characterized by damages and can therefore be considered representative of the behavior of healthy machines, it can be argued that the results obtained with the corrected wind speed are more in line with the expectations about the aging of technical systems.

Table 1: Δ estimate without nacelle wind speed correction.

Year	**T1 (%)**	**T2 (%)**	**T3 (%)**
2012	0.7	1.6	1.5
2013	0.0	-0.7	-0.8
2014	0.6	0.0	1.7
2015	0.4	0.3	0.9
2016	0.9	1.1	2.0
2017	-1.7	-1.4	-1.1
2018	2.7	2.7	3.2
2019	-0.1	-0.9	0.4
2020	-0.7	0.5	0.3
Average	0.3	0.3	0.9
Average up to 2017	0.1	0.1	0.7

Table 2: Δ estimate upon nacelle wind speed correction.

Year	**T1 (%)**	**T2 (%)**	**T3 (%)**
2012	2.1	0.0	-0.6
2013	-0.1	-1.2	-0.5
2014	0.6	0.4	1.1
2015	-0.6	0.0	0.4
2016	0.9	1.4	1.9
2017	-2.0	-2.0	-3.4
2018	2.6	1.5	3.0
2019	-2.0	-1.2	-1.1
2020	-0.4	0.0	1.2
Average	0.1	-0.1	0.2
Average up to 2017	0.1	-0.2	-0.2

5 Conclusions

The present work has been devoted to the formulation of methods for reliably analyzing long term SCADA data sets of wind turbines. The study has been organized as a real-world test case discussion: a decade of data from three 2 MW wind turbines owned by the ENGIE Italia company have been analyzed.

The motivations of this study are in the fact that the analysis of long term SCADA data sets is an interesting objective for the assessment of wind turbine performance decline with age, but in this regard there are several critical points which call for the development of appropriate techniques.

In this work, the aging has been estimated by passing through a Support Vector Regression for the power curve of the wind turbines. By training the regression with the data from the year previous the target and by simulating the output on the target data set, given the input, it is possible to compare how the wind turbine has behaved in the target data set against how it would have behaved if it had been as in the previous year. This procedure has allowed estimating a rate of performance decline with age which can be compared against recent findings in the literature [11] for wind turbine technology of similar size.

As illustrated in Section 1, there are several subtleties in the use of nacelle wind speed measurements for analyzing the power curves of wind turbines. For this reason, an important point of this study is that a statistical procedure for correcting the nacelle wind speed has been formulated and employed prior to the regression for the power curve. The rate of performance decline with age has been computed by using the raw nacelle wind speed measurements and the corrected ones and it results that the latter provide more realistic results. Nevertheless, with both input wind speeds, it is possible to detect that all the wind turbines had a noticeable worsening in 2017 and an improvement in 2018, due to the optimization of the rotational speed control.

These results shed light on possible further directions, which could be related to the incorporation of the most important working parameters in the data-driven regression which is employed for estimating the performance decline with age. On one side, this could improve the robustness of the regression, but on the other side it could introduce further subtleties to take into account. If, as happened also for the test cases of this study, the control of the wind turbine changes at some point in the lifetime of the machine, the regression must be adapted. Therefore, it can be concluded that in general for wind turbine performance monitoring it is important to develop reliable univariate data-driven models for the power curve and, in this context, addressing the critical points of nacelle wind speed measurements is a helpful development.

References

[1] F. Spertino, A. Ciocia, P. Di Leo, S. Fichera, G. Malgaroli and A. Ratclif, "Toward the Complete Self-Sufficiency of an nZEBs Microgrid by Photovoltaic Generators and Heat Pumps: Methods and Applications," in IEEE Transactions on Industry Applications, vol. 55, no. 6, pp. 7028-7040, Nov.-Dec. 2019, doi: 10.1109/TIA.2019.2914418.

[2] F. Spertino, G. Chicco, A. Ciocia, G. Malgaroli, A. Mazza and A. Russo, "Harmonic distortion and unbalance analysis in multi-inverter photovoltaic systems," 2018 International Symposium on Power Electronics, Electrical Drives, Automation and Motion (SPEEDAM), 2018, pp. 1031-1036, doi: 10.1109/SPEEDAM.2018.8445358.

[3] M. Lydia, S.S. Kumar, A.I. Selvakumar and G.E.P. Kumar, "A comprehensive review on wind turbine power curve modeling techniques", Renewable and Sustainable Energy Reviews, vol. 30, pp. 452-460, 2014.

[4] A. Honrubia, A. Vigueras-Rodríguez and E. Gómez-Lázaro, "The influence of turbulence and vertical wind profile in wind turbine power curve", Progress in turbulence and wind energy, vol. IV, pp. 251-254, 2012

[5] C.M.S. Martin, J.K. Lundquist, A. Clifton, G.S. Poulos and S.J. Schreck, "Atmospheric turbulence affects wind turbine nacelle transfer functions", Wind Energy Science, Vol. 2(1), pp. 295-306, 2017

[6] IEC 61400-12-1:2017 - Power performance measurement of electricity producing wind turbines.

[7] A. Carullo, A. Ciocia, P. Di Leo, F. Giordano, G. Malgaroli, L. Peraga, F. Spertino, and A. Vallan, "Comparison of correction methods of wind speed for performance evaluation of wind turbines", Proc. of 24th IMEKO-TC4 International Symposium, 2020 September 14-16, pp. 291-296.

[8] A. Carullo, A. Ciocia, G. Malgaroli, and F. Spertino, "An Innovative Correction Method of Wind Speed for Efficiency Evaluation of Wind Turbines", ACTA IMEKO 2021, Under review.

[9] I. Staffell and R. Green, "How does wind farm performance decline with age?", Renewable energy, Vol. 66, pp. 775-786, 2014

[10] J. Olauson, P. Edström and J. Rydén, "Wind turbine performance decline in Sweden", Wind Energy, Vol. 20(12), pp. 2049-2053, 2017

[11] S.D. Hamilton, D. Millstein, M. Bolinger, R. Wiser and S. Jeong, "How does wind project performance change with age in the United States?", Joule, Vol. 4(5), pp. 1004-1020, 2020

[12] R. Byrne, D. Astolfi, F. Castellani and N. J. Hewitt,"A Study of Wind Turbine Performance Decline with Age through Operation Data Analysis", Energies, Vol. 13(8), n. 2086, 2020

[13] D. Astolfi, R. Byrne and F. Castellani,"Analysis of Wind Turbine Aging through Operation Curves", Energies, Vol. 13(21), n. 5623, 2020

[14] D. Astolfi, R. Byrne and F. Castellani, "Estimation of the Performance Aging of the Vestas V52 Wind Turbine through Comparative Test Case Analysis", Energies, Vol. 14(4), n. 915, 2021

[15] H.G. Kim and J.Y Kim, "Analysis of Wind Turbine Aging through Operation Data Calibrated by LiDAR Measurement", Energies, Vol. 14(8), n. 2319, 2021

[16] A. Carullo, A. Castellana, A. Vallan, A. Ciocia and F. Spertino, "In-field monitoring of eight photovoltaic plants: Degradation rate over seven years of continuous operation", ACTA IMEKO, Vol. 7(4), 2018

[17] L. Jr Mishnaevsky and K. Thomsen, "Costs of repair of wind turbine blades: Influence of technology aspects", Wind Energy, Vol. 23(12), pp. 2247-2255, 2020

[18] V. Cocina, P. Di Leo, M. Pastorelli, and F. Spertino, "Choice of the most suitable wind turbine in the installation site: A case study," 2015 International Conference on Renewable Energy Research and Applications (ICRERA), Palermo, 2015, pp. 1631-1634.

[19] C. MacEachern and İ. Yıldız, "1.16 Wind Energy," Comprehensive Energy Systems, 2018, pp. 665-701.

[20] P. J. Davis, "Leonhard Euler's Integral: A Historical Profile of the Gamma Function", American Mathematical Monthly, vol. 66, Issue 10, 1959, pp. 849-869.